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A Novel Fuzzy Self Tuning Technique of Single Neuron PID Controller for Brushless DC Motor

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ABSTRACT

In this paper, a combination ANN/Fuzzy technique is used to design a Novel Fuzzy Single Neuron PID (NFSNPID) controller to achieve high performance brushless DC motor. The design steps include two parts. The first part uses the genetic algorithm (GA) to find the optimum parameters of Single Neuron PID (SNPID) controller, while the former deals with the design of fuzzy logic control to update the weights of SNPID control online. To demonstrate the designed controller effectiveness, a comparative study is made with between the NFSNPID, Conventional Fuzzy Single Neuron PID CFSNPID and SNPID. All controllers were used to drive, separately, the brushless DC motor against the sudden change of load and operating speed. The performed simulations show better results that motivate for further investigations.

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1. INTRODUCTION

It is known that the BLDC motors is a kind of permanent magnet synchronous motors. This type of motors is driven by six-step inverter, but current commutation is obtained by solid-state switches. The commutation instant depends on the rotor position which is sensed either by hall effect sensors or by sensorless techniques [1]. The BLDC motors have many merits such as long running period, fast dynamic response, low losses, high speed scale and proportional relationship between speed and torque of motor [2].

Therefore, the BLDC motor has been used in many industrial applications such as roll steel mills, robotics, electric automotive and aviation in such applications BLDC motor exposed to many kinds of load disturbances [3]. Conventional control methods cannot achieve the desired speed tracking with good accuracy in case of sudden disturbance and parameters variation [4]. The PID controller is a linear controller and widely accepted because of its simple scheme and excellent performance. It represents a good candidate for different industrial applications [4, 5]. It is known by its elimination of the error in steady-state. Its gains are tuned to assure both stability and performance. For such purpose, several design techniques were suggested in particular, intelligent techniques (Genetic Algorithm (GA), Evolutionary Programming (EP), and Simulated Annealing (SA), etc..) [6-8] and animal mimics (Bacterial Foraging Algorithm (BFA), Bee's Algorithm (BA), Particle Swarm Optimization (PSO), etc...) were studied [9-11].

Another type of PID controller is the single neuron PID that can be enhanced the performance of conventional PID controller. The single neuron controller has the characteristics of adaptive, self-learning, on-line adjustment and relative lower requirements for stability and precision of controlled objects. Moreover, the structure of the single neuron PID controller is simple and reliable [6]. In the beginning, the initial values of SNPID control parameters can be determined by try and error and this takes a long time of

simulation. Now, the tuning optimization techniques (GA, PSO and ant colony (ACO)) used usually relies on the computation of an objective function representing the desired performance while satisfying the system constraints.

The weights adjusting method of SNPID control is highly affected on the control performance [8]. There are various weights-learning algorithms based on the learning theory of neural network such as supervised delta learning rules, non-supervised Hebb learning rules, improved Hebb learning rule and supervised Hebb learning rule [8]. Sometimes, the learning theory of neural network algorithms take a long time to adapt the weights of SNPID control when the system exposed to any disturbance [5,9]. Performance characteristics of an improved SNPID controller using additional error of an inverse control signal is presented in [5, 10]. PID based on a single artificial Neural Network algorithm for intelligent sensors are demonstrated in [8]. Single Neuron PID control of aircraft deicing fluids rapid heating system is implemented in [9]. Single Neuron adaptive PID control for Hydro-viscous drive cutch are demonstrated in [11]. In this paper the GA is used to find the optimum values of SNPID controller parameters based on square error objective function [7].

The fuzzy logic control system based on expert knowledge database has less calculations in taking its decision and suitable for applications where processes with modeling difficulties, either because it is unknown or it has a lot of adjustable parameters [6,9]. So, in this paper the SNPID control is combined with self-tuning fuzzy logic control to introduce a novel method to adjust the weights of SNPID control accurately which make the system more robustness against any disturbances. The main contribution of this paper design a NFSNPID and comparing it with CFSNPID and SNPID controllers to achieve high performance BLDC motor drive system. The rest of this paper is arranged as follows: Section II presents the dynamic modeling of BLDC motor. The SNPID control techniques are included in Section III. Section IV provides the simulation results. Recently, Section V concludes.

2. DYNAMIC MODEL OF BLDC MOTOR

The transfer-function based on mathematical models are usually used in automatic control fields. Some control design and analysis methods, such as the root-locus method and the frequency-response method are developed based on the system transfer function [12]. The transfer function of the BLDC motor at no load may be written as follows [12]:

$$G_u(S) = \frac{\omega(S)}{U_d(S)} = \frac{K_T}{L_a J S^2 + (r_a J + L_a B_v)S + (r_a B_v + K_e K_T)} \quad (1)$$

Where:

U_d: DC voltage.
r_a: Line winding resistance.
L_a: Equivalent line winding inductance.
J: Motor moment of inertia.
ω: Motor rotor speed.
B_v: Viscous constant.
K_e: Line back-EMF constant.
K_T: Line torque constant.

The BLDC motor drive system is demonstrated as block diagram in Figure 1. The main components of drive system contain of six step voltage source inverter, logic circuit, and three hall effect sensors.

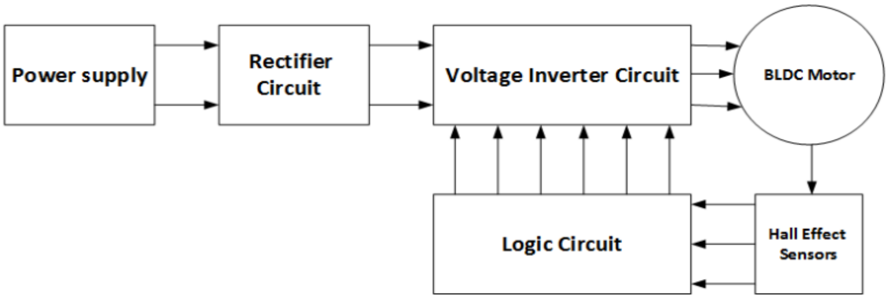

Figure 1. Brushless DC motor drive system.

Table 1. The BLDC Motor Parameters.

Rating	Symbol	Value	Units
DC resistance	R	0.57	Ω
Inductance	L	1.5	mH
Torque constant	K_T	0.082	N.m/A
No. of Poles	P	4	
Rated torque	T_p	0.42	N.m
Rated Voltage	V	36	V
Rotor Inertia	J	$23e^{-6}$	Kg.m2
Friction coefficient	B_v	0.0000735	N.M.S
Rated Speed	ω	4000	RPM
Rated current	I	5	A

The parameters of the BLDC motor are listed in table 1. Figure 2 illustrates the open loop response of BLDC motor drive system model. It can be noted that at time 0.1 sec the BLDC motor exposed to sudden load correspond 50% of rated torque, the rotor speed will be reduced to 3200 RPM. Figure 3 shows the corresponding phase current of BLDC motor. It can clear that the starting current rises to 18 A in a small time, while through the sudden load at time 0.1 sec the phase current will be increased to ±2.5 A.

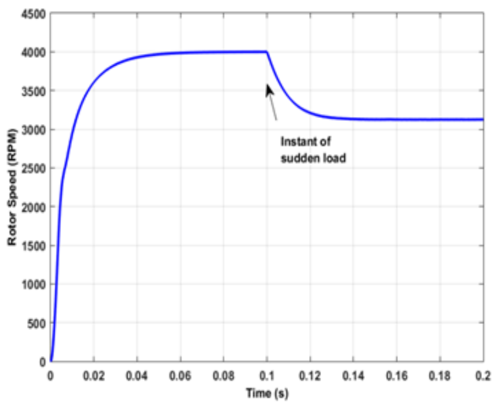

Figure 2. Open loop response of BLDC motor drive system model

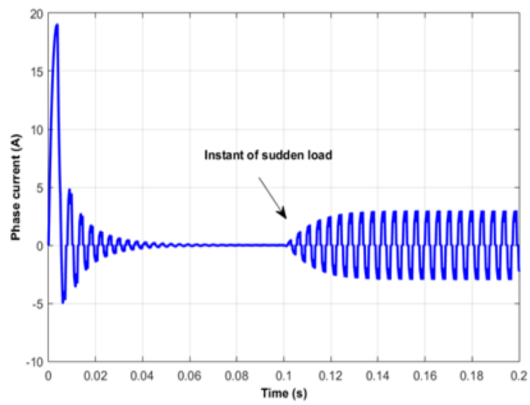

Figure 3. The corresponding phase current of BLDC motor model

3. CONTROL TECHNIQUES

This section discusses the structure of three different control techniques based on the SNPID control where the first control technique uses the GA to find the optimum parameters of SNPID control [5], while the second control technique is the self-tuning fuzzy logic control to update the weights of SNPID control proposed in [6]. The third one is a new hybrid control technique which combines the SNPID control and the fuzzy PID control. The continuous-time traditional PID represent as:

$$u(t) = k_P\, e(t) + k_I \int_0^t e(t)dt + k_d \frac{de}{dt} \tag{2}$$

Where u(t) is the controller output and e is the controller error. The discretization can be performed by differentiating both sides of eq (2) as:

$$u(t) = k_P\, e(t) + k_I\, e(t) + k_d \frac{de}{dt} \tag{3}$$

Applying the backward diff. method on eq (3) gives:

$$u(k) - u(k-1) = k_P\,[e(k) - e(k-1)] + k_I\,[\,e(k)] + k_d[\,\dot{e}(k) - \dot{e}(k-1)] \qquad (4)$$

Applying the backward diff. method again for eq (4):

$$u(k) - u(k-1) = k_P[e(k) - e(k-1)] + k_I\,[\,e(k)] + k_d[e(k) - e(k-1)] - [\,e(k-1) - e(k-2))] \qquad (5)$$

Solving for u (k) finally from eq (5) gives the discrete time PID controller:

$$u(k) = u(k-1) + k_P\,[e(k) - e(k-1)] + k_I\,[\,e(k)] + k_d[\,e(k) - 2e(k-1) + e(k2)] \qquad (6)$$

$$u(k) = u(k-1) + k_P[x_1(k)] + k_I\,[x_2(k)] + k_d[x_3(k)] \qquad (7)$$

$$\begin{gathered} u(k) = u(k-1) + k_P[x_1(k)] + k_I\,[x_2(k)] + k_d[x_3(k)] \\ x_1(k) = e(k) - e(k-1)] \\ x_2(k) = e(k) \\ x_3(k) = e(k) - 2e(k-1) + e(k-2) \end{gathered} \qquad (8)$$

Where $x_1(k)$is a proportional error, $x_2(k)$ is an integral error and $x_3(k)$isadifferential error.

3.1. The SNPID Controller

Single neuron PID (SNPID) is one of the simplest neural network PID that beads on only one neuron. The structure of SNPID controller is illustrative in Figure 4.

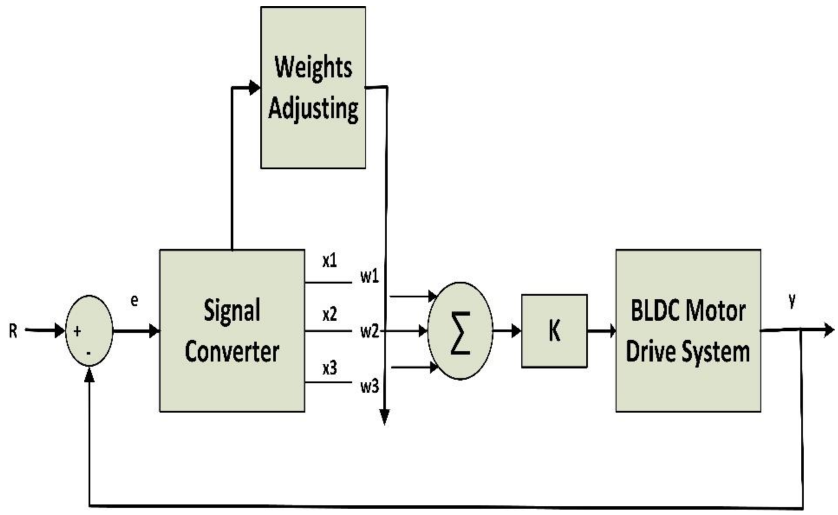

Figure 4. Block diagram of SNPID control.

The SNPIDcontroller can be expressed as:

$$u(k) = u(k-1) + K\,\Sigma\overline{w_i}(k)\,x_i(k) \qquad (9)$$

$$\overline{w_i}\,(k) = w_i(k)/\,\Sigma\ \ |w_i(k)| \qquad (10)$$

The controller output andw_1 , w_2 and w_3 are the neuron weights. There are various weightslearning algorithms based on the learning theory of neural network and the famous algorithm that used in this work issupervised Hebb learning rule.

$$\begin{aligned}(\mathrm{k}) &= w_1(\mathrm{k}-1)+\eta_p x_1(\mathrm{k}-1)\mathrm{u}(\mathrm{k}-1)\mathrm{e}(\mathrm{k}-1)\\ w_2(\mathrm{k}) &= w_2(\mathrm{k}-1)+\eta_i x_2(\mathrm{k}-1)\mathrm{u}(\mathrm{k}-1)\mathrm{e}(\mathrm{k}-1)\\ w_3(\mathrm{k}) &= w_3(\mathrm{k}-1)+\ \eta_d x_3(\mathrm{k}-1)\mathrm{u}(\mathrm{k}-1)\mathrm{e}(\mathrm{k}-1)\end{aligned} \tag{11}$$

Where e is error,η_p ,$\eta_i$and $\eta_d$are proportion learning speed, integral learning speed and differential learning speed.

Genetic algorithm [13], [14] with its main steps (reproduction, crossover, and mutation) is applied to obtain the optimal values of the four parameters that are important in design of the SNPID control, these parameters are K called neuron proportion coefficient and the three learning speed parameters are η_p ,$\eta_i$and η_d. The used cost function as shown in (12) minimizes the integrated square error e (t).

$$f_1=\int_0^{\infty}(e(t))^2\,dt \tag{12}$$

3.1. The CFSNPID Controller

To enhance the robustness and adaptability of the SNPID controller, the fuzzy logic used to design self-tuning SNPID control. The learning rates are critical parameters in design the SNPID control. In the normal SNPID control, it is fixed and the weighted coefficients will increase or decrease in the same proportion to enhance the performances of the controller, the fuzzy logic employed to dynamically adjust the proportional, integral and derivative learning rates. The self-tuning SNPID controller structure is demonstrated in figure 5 [6].

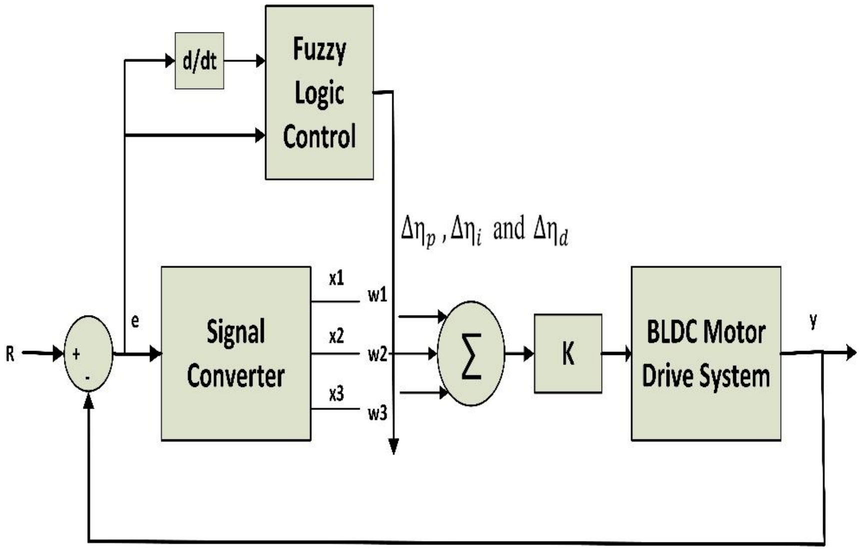

Figure 5. Block diagram of CFSNPID controller.

The weights-learning algorithms of this method are supervised Hebb learning rules as shown in equations 11 and the adjustment of the learning rate are presented as follows:

$$\begin{aligned}\eta_p(\mathrm{k}) &= \eta_p(\mathrm{k}-1)\times\Delta\eta_p(\mathrm{k})\\ \eta_i(\mathrm{k}) &= \eta_i(\mathrm{k}-1)\times\ \Delta\eta_i(\mathrm{k})\\ \eta_d(\mathrm{k}) &= \eta_d(\mathrm{k}-1)\times\Delta\eta_d\ (\mathrm{k})\end{aligned} \tag{13}$$

Where $\Delta\eta_p$,$\Delta\eta_i$and $\Delta\eta_d$ are the outputs of the fuzzy controller.

Both e(t) and Δe(t) can be scaled from [-1,1], and the linguistic labels are {Negative Big, Negative medium, Negative small, Zero, Positive small, Positive medium, and Positive Big} and are referred to in the rules bases as {NB,NM,NS,ZE,PS,PM, and PB}.The linguistic labels of the outputs are {Zero, Medium small, Small, Medium, Big, Medium big, and very big} and are referred to in the rules bases as {Z, MS, S, M, B, MB, and VB}. Figures 6 and 9 show the membership functions of the inputs and the outputs of the fuzzy logic control. The decision making logic simulates the human decision process. The rule bases are simplified in tables 2, 3 and 4. The input e has 7 linguistic labels and Δe has 7 linguistic labels. Hence, there are 49 different rule bases. In this paper, these 49 rule bases have been simplified to 25 rule bases as

discussed in previous work in [15]. The simplification details can be found in [16]. The used defuzzification method is weighted average method.

Table 2. The Rule base of $\Delta\eta_p$.

Δe/e	NB	NS	ZE	PS	PB
NB	VB	VB	VB	VB	VB
NS	B	B	B	MB	VB
ZE	ZE	ZE	MS	S	S
PS	B	B	B	MB	VB
PB	VB	VB	VB	VB	VB

Table 3. The Rule base of $\Delta\eta_i$.

Δe/e	NB	NS	ZE	PS	PB
NB	M	M	M	M	M
NS	S	S	S	S	S
ZE	MS	MS	ZE	MS	MS
PS	S	S	S	S	S
PB	M	M	M	M	M

Table 4. The Rule base of $\Delta\eta_d$.

Δe/e	NB	NS	ZE	PS	PB
NB	ZE	S	M	MB	VB
NS	S	B	MB	VB	VB
ZE	M	MB	MB	VB	VB
PS	B	VB	VB	VB	VB
PB	VB	VB	VB	VB	VB

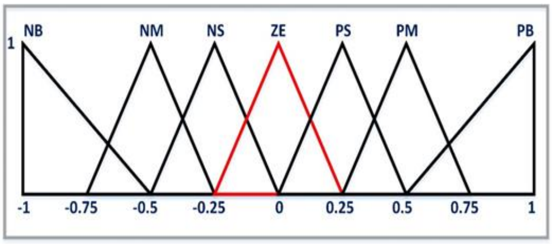

Figure 6. Memberships function of inputs (e, Δe)

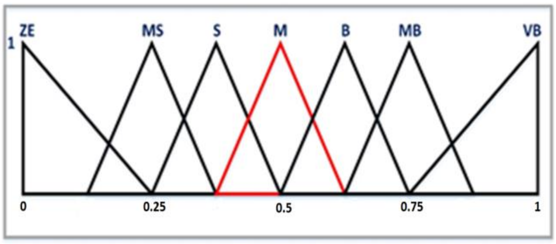

Figure 7. Memberships functions of outputs ($\Delta\eta_p$, $\Delta\eta_i$ and $\Delta\eta_d$)

3.2. The NFSNPID Controller

This work presents a new method of SNPID control. In this the method, the fuzzy logic used to update the weighted coefficients where dynamically adjust of the controller output according to the new formula as following:

$$u(k) = k\left(\left(k_p w_1 e(k)\right) + \left(k_I w_2 \int_0^k e(k)\right) + (k_D w_3 \frac{de(k)}{dk}\right) \quad (14)$$

$$k_p = k_{p1} \times \Delta k_p$$
$$k_I = k_{I1} \times \Delta k_I$$
$$k_D = k_{D1} \times \Delta k_D \quad (15)$$

Where Δk_p , Δk_I and Δk_D are the outputs of the fuzzy controller while, k_{p1}, k_{I1} *and* k_{D1} are the initial values of proportional, integral and derivative gains. The SN fuzzy self-adaptive PID structure of the

proposed method is shown in Figure 8. Figures 6 and 9 show the inputs and outputs memberships of fuzzy logic control while, the rule bases of Δk_p , Δk_I and Δk_D are the same of rule bases of $\Delta\eta_p$, $\Delta\eta_i$ and $\Delta\eta_d$.

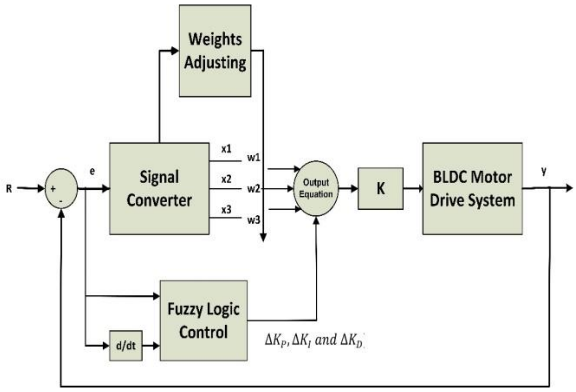

Figure 8. Block Diagram of NFSNPID Control

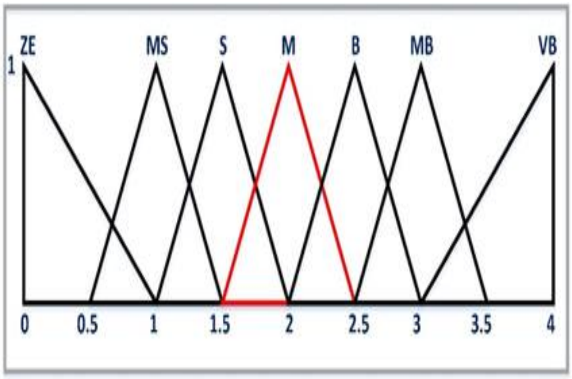

Figure 9. Memberships functions of outputs ($\Delta K_P, \Delta K_I and \Delta K_D$)

4. SIMULATION RESULTS

This section illustrates the simulation results of control techniques applied on BLDC motor drive system. To investigate the robustness of each control technique through the simulation time the BLDC motor will be exposed to sudden change in load and sudden change in operating speed. Figure 10 shows the speed response of each control technique at fixed reference speed 3000 RPM. Also, sudden disturbance is applied on the motor correspond the half of rated torque at time 0.15 sec. It can be noted that the performance of the NFSNPID control has faster response than other control techniques (minimum rise time and low overshoot). Also, it can accommodate the disturbance rapidly. Figure 11 demonstrates the corresponding DC supply current of each control technique. It can be noted that the starting current of NFSNPID control technique is high (18 A) but, at very small time. Also, the current will be increased through sudden load at time 0.15 sec. But, in case of the proposed control technique the current rises quickly compared with other techniques during the sudden load.

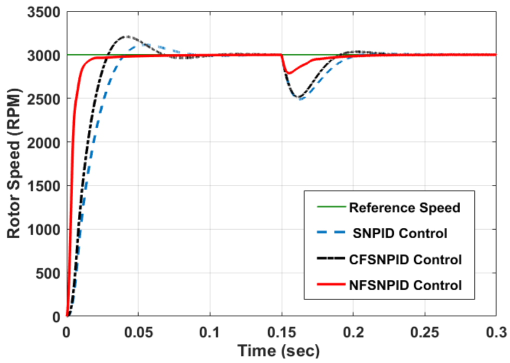

Figure 10. Speed response of control techniques based on SNPID control

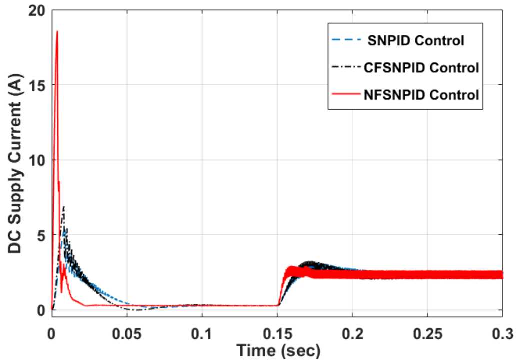

Figure 11. The DC supply current of each control technique at speed regulation

Table 5 summarizes the performance of each control technique based on SNPID control. It is clear that the proposed fuzzy SNPID control has the minimum rise and settling time and acceptable overshoot compared with other techniques.

Table 5. Control Techniques Performance.

Controller method	Rise Time (sec)	Settling Time (sec)	Max. Overshoot %
The SNPID Control	0.0249	0.0711	3.7819
The CFSNPID Control	0.0181	0.0605	6.8886
The NFSNPID Control	0.0074	0.0165	0.0096

A lot of industrial applications the reference speed of BLDC motor is not constant and change continuously such as robotics and electric automotive. So, Figure 12 shows the speed response of each control technique at different commands of reference speed. It is obvious that the NFSNPID control technique can track the reference speed faster than other techniques. Figure 13 illustrates the corresponding DC supply current of each controller technique. It can be noted that at reference speed change the current increases or decreases.

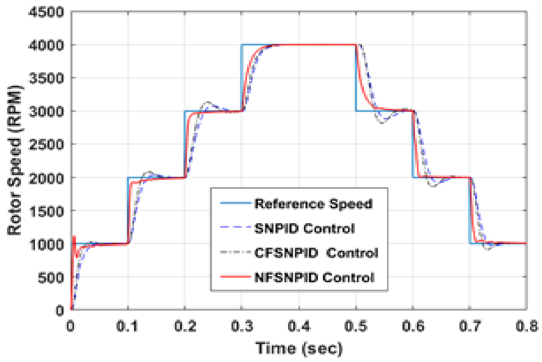

Figure 12. Speed response of control techniques at different commands of reference speed

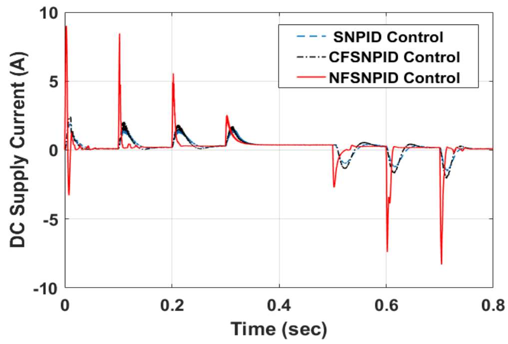

Figure 13. The DC supply current at different commands of speed

5. CONCLUSION

A new self-tuning fuzzy to update the weights of SNPID control online is proposed to achieve high performance brushless DC motor drive system. The genetic algorithm (GA) is used to find the optimum parameters of SNPID controller. The conventional self-tuning fuzzy involves in the simulation showing the effectives of the proposed NFSPID for the motor system. The simulation results have shown that with use of the proposed a new combination of ANN/Fuzzy techniques, the control performance can be remarkably improved.

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